Complex dynamics for the study of neural activity in the human brain

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***Abstract* - Neural mass modeling is a part of computational neuroscience that was developed to study the general behavior of interacting neuronal populations. This type of mesoscopic model is able to generate output signals that are comparable with experimental data such as electroencephalograms. Classically, neural mass models consider two interconnected populations. One interaction have been modeled in two differents ways. In this work we propose and analyze a neural mass model embedding both approaches and compare the generated time series to real data.**

***Index Terms* - Modeling, Simulation.**

I. INTRODUCTION

Computational neuroscience aims at developing new models and methods to improve our understanding of complex relations between structure and function in the human brain. Specifically, mathematical models have been developed to reproduce the complexity of neuronal population activities as accurately as possible and analyzed to identify underlying dynamical mechanisms. The neural mass models, built by considering the essential interactions at a mesoscopic scale, allow us to study the global behavior of neuronal population activities and interaction mechanisms.

II. NEURAL MASS MODEL

The neural mass models (NMM) classically consider interactions between a main population of excitatory pyramidal cells and an inhibitory population of interneurons. These interactions are excitatory and inhibitory feedbacks on the main population. The inhibitory feedback is indirect through the interneurons, the excitatory feedback can be either indirect involving a secondary pyramidal cell population or direct. The model presented here consider all these feedbacks (Figure 1). As in the Jansen-Rit model ([4]), the state variables are the main population excitatory (y_1) and inhibitory (y_2) inputs and its output (y_0). Classically a NMM receives an input $p(t)$ representative of the impact of long-range neural population activities.

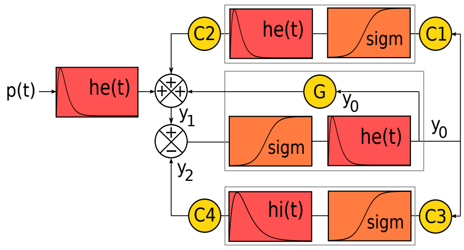

Figure 1: Diagram of the NMM with double excitatory feedbacks. $h_e(t)$ ($h_i(t)$): Action potentials $\rightarrow$ excitatory (resp. inhibitory) post-synaptic potential [1]. sigm: average membrane potential $\rightarrow$ average pulse density [2]. C_i ($i \in [\![1,4]\!]$): coupling gains ($C_i = \alpha_i\, C$, C: maximal number of synaptic connections between two populations) [3]. G: direct feedback coupling gain. $p(t)$: excitatory input.

Following Van Rotterdam work [1], we obtain the following dynamics:

$$\begin{aligned} y_0'' &= A\,a\,\mathrm{sigm}(y_1 - y_2) - 2\,a\,y_0' - a^2\,y_0 && \text{(1a)}\\ y_1'' &= A\,a\,C_2\,\mathrm{sigm}(C_1\,y_0) + A\,a\,G\,\mathrm{sigm}(y_1 - y_2)\\ &\quad - 2\,a\,y_1' - a^2\,y_1 + A\,a\,p(t) && \text{(1b)}\\ y_2'' &= B\,b\,C_4\,\mathrm{sigm}(C_3\,y_0) - 2\,b\,y_2' - b^2\,y_2 && \text{(1c)} \end{aligned}$$

where $\mathrm{sigm}(x) = \frac{2\,e_0}{1+e^{r\,(v_0 - x)}}$.

III. DYNAMICAL ANALYSIS

Four parameters of interest are considered for the dynamical analysis of system (1): p, the single input of the model, C, not quantifiable experimentally and α_2 and G, since direct and indirect excitatory feedbacks play a fundamental role in neural activity.
This analysis allows us to establish that the model can generate five distinct behaviors (Figure 2(a)) which distribution in the rectangle $[G, \alpha_2] \in [0, 80] \times [0, 1]$ is displayed in Figure 2(b).

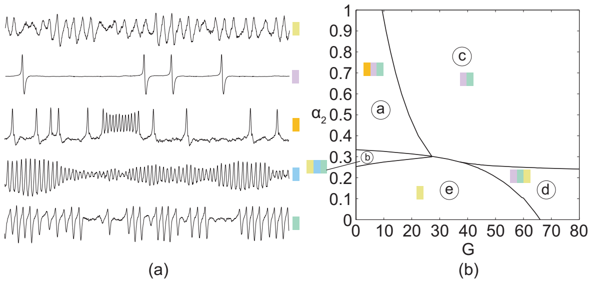

Figure 2: (a) Time series representative of the behaviors of the model identified by specific names and colored flags. Yellow: Noise Modulated Oscillations (NMO). Purple: Noise Induced Spiking (NIS). Orange: Noise Induced Spiking with Over Threshold Oscillations (NIS-OTO). Blue: Noise Induced Thresholded Amplitude Modulation (NITAM). Green: Noise Induced Spiking with Sub-Threshold Oscillations (NIS-STO). (b) Partition of (G, α_2) parameter space gathering in each region the behaviors that can be generated for $(p, C) \in [0, 1000] \times [0, 400]$ [5].

IV. COMPARISON WITH REAL DATA

Using model (1), we have generated time series sharing the essential properties of Hippocampal discharges (HD) occuring in experimental data recorded in epileptic mice (experimental protocole described in [6]). HD are characterized by two typical features: sparse large amplitude oscillations (as the NIS behavior) and rhythmic discharges ressembling to NIS-STO behavior. We have computed both time series spectrograms (Figure 3) showing that the oscillation frequencies are similar in each regime.

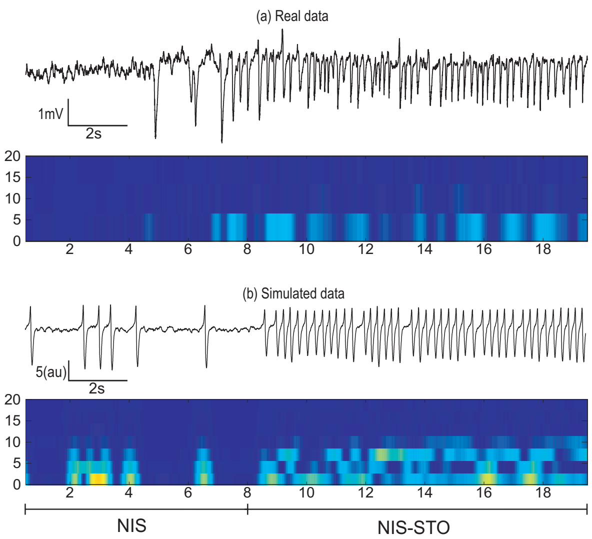

Figure 3: Real (a) and simulated (b) times series and their spectrograms [7].

V. CONCLUSION

We propose a new neural mass model embedding both types of excitatory feedbacks separately used in the literature. We identify the panel of behaviors that the model can generate and study how the "balance" between direct and indirect excitatory feedbacks impacts the dynamical behavior. We show that the model is able to generate time series *in silico* mimicking experimental data.

ACKNOWLEDGMENTS

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